Optimization of Resource Allocation Problems in 5G Network Systems using Nature Inspired Algorithms

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Introduction

With rapid development in mobile networking and communication technologies, the fifth generation (5G) mobile communication systems are highly anticipated to create user centric service oriented and agile networks to meet the diverse user requirements.5G mobile communication system aims to deliver a ubiquitous mobile service with enhanced Quality of Service (QoS). It is also expected to enable new use-cases for various vertical industrial applications-such as automobiles, public transportation, medical care, energy, public safety, agriculture, entertainment, manufacturing, and so on. Rapid increases are predicted to occur in user density, traffic volume, and data rate.

Apart from providing seamless high-data-rate services anytime and anywhere for wide area coverage scenarios, 5G networks are challenged to connect millions of low power and low cost devices and sensors under the limitations and constraints of extremely low latency and high reliability. Reliability, security performance parameters of real time industrial applications such as health care, security and surveillance and interconnected vehicles poses distinct challenges and service requirements to network systems and architectures. Faced with the abundant, distinct, customized service requirements, and in the new application scenarios mentioned above, the network architecture and networking technologies need to be revisited for 5G systems[1].

The key enabling technologies for 5G systems include multi-access edge computing, Cloud Radio Access Network (C-RAN), Network Function Virtualization(NFV), Software Defined Networking(SDN), and Network Slicing and some crucial Radio Access Technologies (RATs), such as Millimeter Wave, Massive Multi-Input Multi-Output(MIMO), Device-to-Device(D2D) Communication, and massive Machine-to-Machine Communication(M2M).

This research proposal reviews the above described enabling technologies for 5G systems and proposes to study the resource allocation optimization problems in some of the above enabling technologies such as multi-access edge computing, network slicing and Cloud Radio Access Network (C-RAN) architectures.

2. Overview of Enabling Technologies for 5G Systems

Driven by the emergence of new compute-intensive applications and the vision of the Internet of Things (IoT), it is foreseen that the emerging 5G network will face an unprecedented increase in

traffic volume and computation demands. However, end users mostly have limited storage capacities and finite processing capabilities, thus to run compute-intensive applications on resource-constrained users has recently become a natural concern. Mobile edge computing (MEC) is a key technology in the emerging fifth generation (5G) network can optimize mobile resources by hosting compute-intensive applications by processing large data before sending to the cloud.

The cloud computing capabilities within the radio access network (RAN) in close proximity to mobile users offer context-aware services. Therefore, MEC enables a wide variety of applications where the real-time response is strictly required, e.g., driverless vehicles, augmented reality, robotics, and immerse media. Indeed, the paradigm shift from 4G to 5G could become a reality with the advent of new technological concepts. The successful realization of MEC in the 5G network is still in its infancy and demands for constant efforts from both academic and industry communities.

Fifth-Generation (5G) systems and network architectures are intended to offer multiple services with diverse set of user requirements and performance specifications. Network Slicing is a process of slicing a single physical network into multiple independent and isolated logical networks. The 5G network design and the standards are still in development, but it is envisioned to be an agile and elastic network. Network slicing has emerged as a key to realizing this vision[2].

Network slicing allows a transition from a network-as-an-infrastructure setup to a network-as-a-service to enable numerous 5G smart services with diverse requirements [3]. In order to provide customized reliable services using limited network resources while reducing capital expenditure and operating expense of 5G networks, network slicing has recently been proposed by the wireless industry as a main enabler of network service convergence and on-demand customized services[4,5,6].

Software Defined Networking (SDN) has been proposed as an emerging network architecture for next generation communication systems, which consists of decoupling the control planes and data planes of a network and provides applications with an abstracted centralized view of the state of the distributed network[7].A logically centralized controller that has a global network view is responsible for all the control decisions and it communicates with the network-wide distributed forwarding elements via standardized interfaces[8]. Due to its openness and standardization, SDN enables

researchers to design and implement new innovative network functions and protocols in a much easier and flexible way[9].

Network Function Virtualization (NFV) has drawn significant attention from both industry and academia as an important shift in telecommunication service provisioning[10]. By decoupling Network Functions (NFs) from the physical devices on which they run, NFV has the potential to lead to significant reductions in Operating Expenses (OPEX) and Capital Expenses (CAPEX) and facilitate the deployment of new services with increased agility and faster time-to-value[11]. Integrated with SDN, the software-defined NFV architecture further offers agile traffic steering and joint optimization of network functions and resources. This architecture benefits a wide range of applications (e.g., service chaining) and is becoming the dominant form of NFV[12].

To build cost effective networks and to provide enhanced QoS to massive end-users, numerous architectures and technologies have been proposed for the Fifth Generation (5G) mobile networks, especially in the domain of Radio Access Network (RAN). We can generally categorize them into the four categories as follows:

- Improving the spectrum efficiency for higher data capacity by deploying advanced transmission techniques such as massive Multi-Input Multi-Output (massive MIMO), Millimeter Wave (mmWave) transmission, and beamforming[13]. There have been significant progresses in the development and deployment of these technologies. However, they are still constrained by major technical challenges, including implementation complexity, Radio Frequency (RF) interference, environmental obstacles, and antenna correlation[14].
- Deploying small cells (pico cells, femto cells, and micro cells) combined with macro cells upon the existing network infrastructure. This approach has been used by Long Term Evolution - Advanced (LTE-A) networks as well, but the heterogeneity level in 5G RAN is significantly higher in comparison to that in legacy RAN architectures. Moreover, the deployment of small cells leads to increases in the power consumption, the CAPEX/OPEX, a variety of interference, and the handover frequency[15,16].

- Applying emerging technologies of Software Defined Network (SDN) and Network Function Virtualization (NFV) to softwarize the networks[15]. However, limitations to the deployment of both NFV and SDN widely exist in security, management, orchestration, isolation, resources allocation, dynamicity, flexibility, and scalability[18,19].
- Optimizing and reconstructing the network architecture specifically the RAN architecture by bringing computation, communication, processing and storage devices close to the edge of networks, so that end-users can access the data and services with low latency and high throughput[20]. However, this approach leads to increased CAPEX/OPEX as well as demands for new protocols and interfaces[21].

In Cloud Radio Access Network (C-RAN) radio and baseband processing functions are split into two separate nodes, namely RRH and BBU. As the amount of user-data has been increasing with regard to various Quality of Service (QoS) requirements, network operators are forced to fulfill these requirements through centralization and cloudification of BBUs and their corresponding RRHs. This new centralized and cloudified RAN, where network resources are pooled in a centralized BBU pool, is known as C-RAN[22,23].

Based on the overview described on the Enabling technologies for 5G systems[17], in this research study, we would like to address the Resource allocation optimization problems pertaining to some of the key enablers of 5G mobile communication system the details of these problems follow in the next section.

3.Literature Review of the Resource allocation optimization problems pertaining to some of the key enablers of 5G mobile communication system

In this section a detailed review and the problem statement of the Resource allocation optimization problems pertaining to some of the key enablers of 5G mobile communication system are discussed.

3.1 Optimization of Energy Consumption in Mobile Devices by Efficient Computational Offloading and Optimal Resource Allocation in Multi-Tier Multi-Access Edge Computing Systems in 5G Heterogeneous Networks

The new mobile computing services/ applications generate large amount of data on the telecommunication networks and also require high computing capacity. But most mobile devices have

limited computing capacity, limited battery power and limited storage space. Multi-access Edge (MEC) Computing is a promising solution to mitigate this limitation wherein offloading of the computational processing of the MD to the MEC servers allows processing of these heavy computational tasks of the Mobile devices on the MEC Servers[24,25,26,27]. This not only conserves the battery power of the mobile device and frees them from heavy computing tasks but also reduces the latency as the processing is happening in the MEC server which is close to the end user. However, due to the resource limitations of the MEC server, such computation offloading from MDs to MEC Servers remains a challenge. Therefore, offloading calculations strategies and optimization of resource allocations including the MEC computing resources and transmit power are required to improve the performance of Computation Offloading[27].

In modern telecommunication networks Heterogeneous Networks (HetNets) are used to address the issue of exponential increase in data traffic. HetNet comprises of a combination of different cell types and different access technologies. In HetNet a homogeneous macro cell base station is overlaid with low power small cell base stations such as femto cell, pico cell and micro cellso as to ensure proper coverage as well as enhance data handling capacity of the network[28]. Operators can potentially provide a more consistent customer experience compared to what could be achieved with a homogenous network, by integrating a variety of technologies and cell layers depending on the topology of the coverage area. A seamless transition between the different layers and different radio interfaces takes place, without requiring the user to do anything.

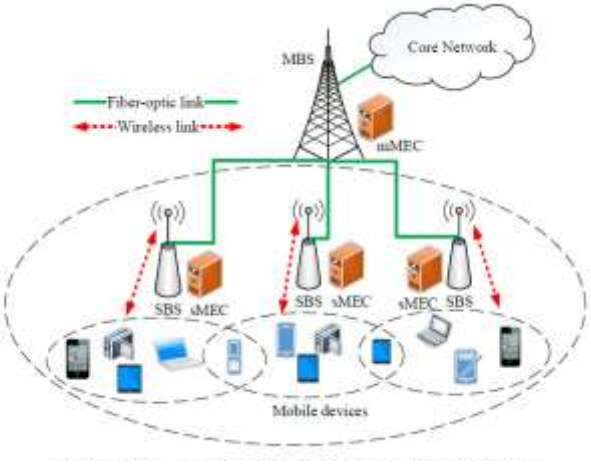

Fig1: Multi-tier computation-offloading strategy in HetNets[29]

In Fig1 – Mobile devices (MDs) having limited computational capacity and randomly deployed. These mobile devices directly connect to the small cell base stations (SBSs) to offload their computational task(s). These small base stations connected to the macro-base stations (MBS) through fiber-optic links[30,31]. The small base stations and macro-base stations are integrated with mobile edge computing servers providing computational task(s) to mobile devices.

Authors[29] defined the mobile edge computing servers co-located with the macro-base stations and the small base stations as mobile base stations- mobile edge computing (mMECs) and small cell base stations – mobile edge computing (sMECs), respectively. The mobile devices connect to the small base stations, which enable latency reduction and increases data rates.

In recent time integrating MEC into 5G networks to increase network performance, to reduce power consumption in MDs, and to utilize macro and small cells has generated a lot of research interest. Thus, recent studies have focused on computational offloading in 5G networks[32], and use of single-tier MEC servers and multi-tier MEC servers in HetNets. However, achieving effective offloading decisions related to computation- completion time and energy in a multi-tier MEC server is an important optimization problem that attracts considerable attention of the researchers.

To this end, in[30] have proposed, a two-tier computational- offloading framework for multi-user multi-server MEC in 5G HetNets and considered a joint Resource Allocation and Computational Offloading problem that minimizes the total computing overhead of MDs including completion time and energy consumption. This optimization problem was formulated as a mixed-integer nonlinear program problem and is of NP-hard complexity having both continuous (resource allocation) and discrete (offloading decision) variables. This is a difficult and complex problem that cannot be solved optimally in polynomial time and therefore has attracted the use of a NIC technique. It was solved using Particle Swarm Optimization and obtained promising results in terms of total computing overhead and solution convergence compared to several baseline schemes. In[33] have proposed, offloading decisions and small base stations (SBS) associations are jointly optimized with transmission power and channel assignments in a small cell cellular network. The objective is to minimize the total energy consumption of all mobile devices (MDs) for latency constraints. The problem is first formulated as a mixed binary nonlinear programming problem, then transformed and

solved using the general bender decomposition (GBD). A heuristic solution is proposed that recursively allows more mobile devices (MDs) to make offloading decisions based on the current transmission conditions. Compared to using general bender decomposition, this solution results in much lower worst-case complexity, while achieving good energy performance for a wide range of system parameters.

Based on the recent studies in Nature Inspired Computing (NIC), it has been observed that different variants of Particle Swarm Optimization (PSO) techniques with multiple hybridization schemes of various NIC techniques have performed much better than standard PSO on continuous and discrete optimization problems[96]. This motivates us to explore the use of more recent NIC like Ant Colony Optimization [86,87], Social Evolution[93], Artificial Bee Colony Optimization Algorithm[85], Whale Optimization Algorithm[73], Biogeography Based Optimization (BBO)[72] and their hybrid variants for the solution of this problem.

For solving the above problem, simulated datasets from[29] will be considered for constructive performance evaluation studies. Where ever required we will also synthesize additional datasets with different complexities for further analysis.

3.2 Resource Allocation Scheme for 5G Cloud Radio Access Network (5G-CRAN)

With the emergence of 5G telecommunication networks the amount of data traffic traversing networks is exploding. This forces the telecom operators to add more cells into existing networks by creating Heterogeneous and Small cell networks or by integrating Multiple Input Multiple output (MIMO). However, the deployment of additional cells leads to steep increase in Capital Expenditure (CAPEX) and Operational expenditure without proportionately increasing the revenues of the service provider. Moreover, the urban areas already have a high density of base stations therefore, adding more base stations is difficult. One of the ways network operators are coping with this reality is to transform the radio access network (RAN) into a centralized one by placing it in the cloud called Cloud Radio Access Network C-RAN[24,25,26]. The C-RAN decouples the baseband processing unit (BBU) from the remote radio head (RRH) by allowing BBUs from multiple Base Stations (BSs) to operate into a centralized BBU pool on a remote cloud-based infrastructure and a scalable deployment of light-weight RRHs. Thus, a C-RAN architecture has three primary components — a centralized

baseband unit (BBU) pool, remote radio unit (RRU) networks, and transport network or fronthaul[34,35,36]

BBU Pool — The BBU pool, located at a centralized site, functions as a cloud or a data center. Its multiple BBU nodes dynamically allocate resources to RRUs based on current network needs. These implement the functionality of the MAC layer.

RRU Network — The wireless RRU network connects wireless devices similarly to access points or towers in traditional cellular networks. They integrate the Radio Frequency (RF) frontend functions capable to acquire, process and transmit the signal.

Fronthaul/Transport Network — Using optical fiber communication, cellular communication, or millimeter wave (mmWave) communication, the fronthaul is the connection layer between a BBU and a set of RRUs, providing high-bandwidth links to handle the requirements of multiple RRUs.

Thereby, a BBU can be assigned to one or more RRHs. Similarly, by sharing their radio resources, a number of RRHs managed by a single BBU can form a single cluster especially for reducing the cost of maintenance, the computational load and for energy saving purpose. Furthermore, besides being reliable and relatively inexpensive, solutions for the interconnection of BBUs must allow high bandwidth and flexible topology for the interconnection of RRHs.

In other words, in the C-RAN architecture, treatments are moved from BSs toward the cloud, which is based on open platforms and has better virtualization capabilities for dynamic allocation of available resources[34,35,36].

In traditional architectures only about 15-20%of BSs operating in the current RAN architecture are loaded more than 50% [37,38] resulting in wastage of power in current RAN. Thus, by shifting computing resources of BSs and radio communication features to cloud, allow the reduction of energy consumption and upgrading costs while enabling resource sharing and a coordinated joint signal processing in order to increase the spectral efficiency. This approach allows the reduction of OPEX since the computational load and the energy consumption are reduced compared to the traditional architecture.

Thus the C-RAN can lower the total cost of ownership (TCO), improve network performance, has the ability to pool resources, reuse infrastructure, simplify network operations and management,

support multiple technologies, reduce energy consumption, and lower CAPitaleXpenditure (CAPEX) and OPErationalEXpenditure (OPEX). The centralized cloud RAN architecture also provides the benefit of not requiring a rebuild of the transport network. The C-RAN will also have other benefits, such as easier and faster network deployments and increased network flexibility.

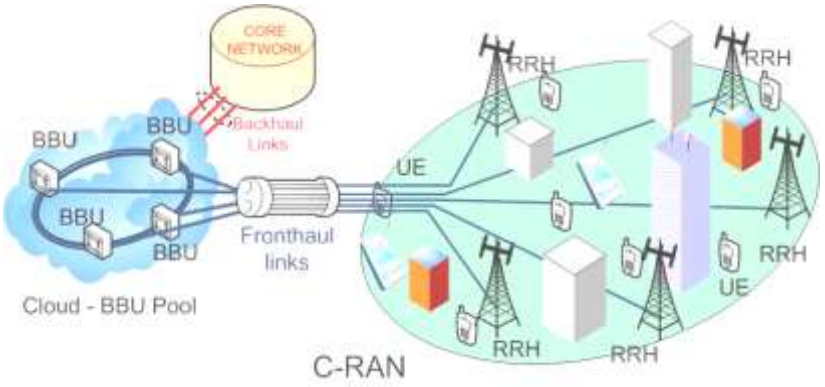

Fig2 – Cloud - Radio Access Network (C-RAN) Architecture[97]

However, in C-RAN the challenging issue is designing a logical joint mapping between User Equipment and RRHs as well as between RRHs and BBU. This is done dynamically taking into consideration the network load conditions in a way to reduce the overall network costs while maintaining the user Quality of Service (QoS) and Quality of Experience (QoE). This is a two-stage resource allocation problem where the first stage is UE-RRH association and the second stage is RRH-BBU mapping.

In Cloud-Radio access network (C-RAN), the baseband units (BBUs) of all base stations (BSs) is centralized forming a virtualized Base band unit pool, which is then shared among the BSs[39,40,41].

A number of studies exist in the literature that dealt with the issue of UEs association and the RRHs mapping with BBUs but most of them addressed the problem separately even though these problems are dependent and have to be dealt jointly.

The emerging trend is to solve the resource allocation optimization problems in 5G-C-RAN using Nature Inspired Computing methods. A number of Nature Inspired Computing methods including Particle Swarm Optimization (PSO)[84], Genetic Algorithm (GA)[78], Ant Colony Optimization (ACO)[86,87] and Artificial Bee Colony (ABC)[48], have been used to solve various optimization problems.

Recently, in[42] addressed, this problem by jointly considering the problem RRH antenna with the BBU computation resources and proposed a power efficient resource allocation scheme for optimal C-RAN systems named Bee-Ant-CRAN. They designed a scheme for real time UE-RRH and RRH-BBU mapping jointly for resource allocation in 5G C-RAN as a multi-objective optimization problem with a number of constraints, based on a modified approach of ABC and ACO metaheuristics. This multi-objective optimization problem is formulated as mixed integer nonlinear problem and is NP-hard. Their method obtained promising results in terms of reducing the resource wastage and significantly improving the spectral efficiency as well as throughput. In[43] have proposed, Cloud Radio Access Network (C-RAN) to reduce operational costs and ensure service quality to solve these problem by handling traffic and mobility in a centralized manner. Separating baseband units (BBUs) from base stations (RRHs) and sharing BBUs in a pool. The key problem in C-RAN optimization is to dynamically allocate BBUs and map them to RRHs under cost and quality constraints. In this paper, a data-driven framework for C-RAN optimization. Firstly, a deep-learning-based Multivariate Long Short Term Memory (MuLSTM) model to capture the spatiotemporal patterns of traffic and mobility for accurate prediction. Secondly, formulate RRH-BBU mapping with cost and quality objectives as a set partitioning problem, and propose a Resource-Constrained Label-Propagation(RCLP) algorithm to solve it. The greedy Resource-Constrained Label-Propagation(RCLP) algorithm is worst-case approximation guarantee to optimal. The results show that high quality outperforming baselines.

This motivates us to explore the use of more recent NIC like Ant Colony Optimization[86,87], Social Evolution[93], Artificial Bee Colony Optimization Algorithm[48], Whale Optimization Algorithm[73], Biogeography Based Optimization (BBO)[72], Quantum Inspired Evolutionary Algorithm[75]and their hybrid variants for the solution of this problem.

Most of the existing resource allocation schemes in C-RAN are not yet capable of taking the full advantage of the concept of centralized virtual BSs. The large scale RRHs and BBUs resource allocation problem still needs to be considered.

For solving the above problem, simulated datasets from[42] will be considered for constructive performance evaluation studies. Where ever required we will also synthesize additional datasets with different complexities for further analysis.

2.3 Optimization of Inter-Slice Resource Management in 5G Network using Nature Inspired Computing Techniques

Network slicing is one of the important problems in 5G networks. The Network Slicing problem is first proposed by Next Generation Mobile Networks (NGMN)[51]. The network slicing problem is all about managing multiple independent logical networks on a common physical infrastructure where each slice operates a specific business requirement with certain Quality Of Service (QoS). Network slicing not only improves the performance of specialized applications but also benefits the mobile network operators (MNOs) with increased business profits [52]. Network slicing problem can be applied on physical infrastructure resources as well as on virtualized resource blocks i.e. computational capacity[53] based on the requirement of the business case. The resource blocks can be homogeneous (resource blocks from the same server or server cluster) or heterogeneous (frequency bands and transmission power) in nature. In both homogeneous and heterogeneous based use cases, each slice will have different utility efficiencies. For example, with the same amount of resource, slices for mobile broadband (MBB) services require high average user throughput, while slices for massive Machine-Type Communication (mMTC) services focus more to simultaneously serve more low-traffic devices[54]. According to[55], even with the same service type, elastic slices can be defined to guarantee an average QoS level for a lower payment, while in elastic slices provide guaranteed minimal QoS level for a higher payment. This approach is usually known as “Slice as a Service” (SlaaS)[56].

Technically, SlaaS can be considered as a specific form of cloud computing resource management techniques such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). Since over a decade, various approaches have been proposed to schedule and allocate physical and logical resources over different cloud clients[57,58]. In the classical cloud computing domain, it usually considers mostly homogeneous instances and simple resource pool in classical

public cloud environments, which simplifies the resource constraints to one-dimensional or two-dimensional[50].

The challenging aspect of Network slicing in 5G networks is to optimize the long-term network utility in Slice as a Service (SlaaS) with a good scalability and reach Quality of Solutions (QoS). In 5G networks, as indicated in[59], a large number of slice types can be required to support highly heterogeneous mobile services, and the dimension of resource pool can also be considerably large. These can lead to a high computational complexity of global optimizing algorithms with cascaded loops such as [60], and reduce their feasibilities. Depending on the use scenario, different slices in 5G networks can even have highly heterogeneous constructions of the utility function. For instance, the energy efficiency is a critical term in the utility function of mMTC slices, the delay is more important for ultra low-latency reliable communications (URLLC) slices, while the MBB slices are more evaluated regarding the throughput[50].

Classical cloud resource allocating approaches that mostly consider one or few homogeneous cost functions, such as power[61], throughput[62] or resource utilization rate[63], for all instances, can be hardly applied in 5G SlaaS. Novel methods are therefore called for, which are expected to be flexible with various constructions of resource constraints and heterogeneous utility functions.

Many researchers have proposed different models to address the network slicing problem. Some of the most prominent ones include, profit optimization model for sliced mobile networks that applied on the traditional business model[59] where, the problem is modelled as a classical multi-objective optimization problem (MOOP) to solve the optimal resource allocation to find a satisfactory solution for getting profit. In[55], proposed online Genetic Algorithm based models to address heterogeneous slices with Quality of Service (QoS) requirements in 5G networks and demonstrated the effectiveness of online Genetic Algorithm model when compared with other existing methods interns of optimum results, rate of convergence.

In[64,65,66] Machine Learning and Deep learning models such as Deep reinforcement learning and DeepCog models were proposed to address the challenges in Network slicing problems. In[67], for heterogeneous networks, a Heterogeneous cloud-radio access networks (H-CRAN) model was

proposed considering a virtualized backhaul network to solve the resource management by applying mathematical models and heuristic techniques.

In[55], have proposed to obtain the global optimum of inter-slice resource management, a Value Iteration approach, and a novel Q-Learning online machine learning algorithm were also proposed and the effectiveness of Q-Learning algorithm was demonstrated in the utility function, with minimum computational cost while approximating the optimal performance. In[68], have proposed a novel online genetic slicing optimizer to maximize the long-term network utility in SlaaS. It has been evaluated through numerical simulations for global optimum. It encodes slicing strategies instead of resource schedules into binary sequences, which enables genetic optimization for inter-slice resource management. Recently in[69] have proposed evaluate a Cross Layer Controller (CLC), which acts on top of SDN and SDR technologies, and monitors in real-time the conditions in the radio environment as well as the transport network traffic, in a unified way. Based on this dynamic input, CLC enforces end-to-end resource allocation policies and pairing mechanisms between network slices from different network segments. The experimentation results demonstrate the considerable gains acquired from the proposed solution.

From the above description, it can be observed that, the evolutionary algorithms and machine learning variants have provided better insights in solving the networking slicing problems in heterogeneous environment. It is also observed that, very little swarm intelligent variants have been adopted in addressing the above problem. In this research study we would like to explore to apply some of the most promising Nature Inspired Algorithm variants like Ant Colony Optimization[86,87], Social Evolution [93], Artificial Bee Colony Optimization [48], Whale Optimization Algorithm[73], Biogeography Based Optimization[72], Quantum Inspired Evolutionary Algorithm[75] and their hybrid variants to address the networking slicing problems.

Hybrid PSO and Quantum-I*nspired* Evolutionary Algorithm (QIEA) have demonstrated better results in terms of objective function values and computational time compared to traditional Genetic Algorithms[70]. In this research study we would like to explore to apply some of the most promising Nature Inspired Algorithm variants to address the networking slicing problems.

For solving the above defined networking slicing problem, simulated datasets from[50] will be considered for constructive performance evaluation studies. Where ever required we will also synthesize additional datasets with different complexities for further analysis.

Based on the detailed discussed on the different problems, the potential research objectives are described in the next section.

4. Research Objectives

1. To conduct an extensive literature review and empirical survey on application of Nature Inspired Computing techniques in resource allocation optimization problems in Fifth Generation(5G) networks and systems.

2. Optimization of Energy Consumption in Mobile Devices by Efficient Computational Offloading and Optimal Resource Allocation in Multi-Tier Multi-Access Edge Computing Systems in 5G Heterogeneous Networks using Nature Inspired Computing Techniques.

3. Optimization of Resource Allocation Scheme for 5G Cloud Radio Access Network (5G-CRAN) using Nature Inspired Computing Techniques.

4. Optimization of Network Slice Resource Management problem in heterogeneous environment in 5G Networks using Nature Inspired Computing Techniques.

For the above research objectives 2, 3 and 4 some of the below described nature inspired computing algorithms will be considered.

- Particle Swarm Optimization and its hybrid variants[71],
- Artificial Bee Colony Optimization and its hybrid variants[72],
- Biogeography Based Optimization(BBO)[73],
- Whale Optimization Algorithm(WOA)[74] and
- Quantum Inspired Evolutionary Algorithm[75].

5. Research Methodology

As described in Section 3, as part of this research study, we would like to explore the application of some of the most successful, efficient and recent natured inspired computing algorithms to the selected Resource Allocation optimization problems in 5G as mentioned above. The details on the Nature Inspired Computing Techniques can be found in section 5.1. In section 5.2 describes the

datasets used for comparing the proposed algorithms with the standard algorithms reported in the literature for qualitative performance analysis.

The objectives 2, 3 and 4 being complex nonlinear NP-hard problems they need to be solved using NIC techniques. The following NIC techniques have been chosen for the solution of the selected problems as they are competent and have demonstrated good performance on a number of other optimization problems.

- Particle Swarm Optimization and its hybrid variants[71]
- Artificial Bee Colony Optimization and its hybrid variants[72]
- Biogeography Based Optimization(BBO)[73],
- Whale Optimization Algorithm(WOA)[74]and
- Quantum Inspired Evolutionary Algorithm[75]

The efficacy of the NIC methods implemented for the solution of the selected problems will established by testing them on the data sets used by earlier researchers so as to enable comparison of the performance in terms of quality of the obtained solutions, number of evaluations, and rate of convergence.

Section 5.1 introduces Nature Inspired Computing Techniques in detail. Section 5.2 describes the datasets that will be used for evaluating the performance of the implemented NIC techniques and comparing them with the algorithms reported in the literature for qualitative performance analysis.

5.1.Nature Inspired Computing (NIC) Algorithms

Nature inspired computing (NIC) is an emerging computational methodology that builds on the principles of emergence, self-organization and complex systems [76]. Some of the important objectives of the nature inspired computing paradigm are study of natural phenomena, modelling of natural phenomena and also to provide alternative stochastic, nature inspired search based techniques to address problems that have not been (satisfactorily)resolved by traditional deterministic algorithmic techniques[77]. Some of the most successful algorithms inspired by the natural phenomena are:

Evolutionary algorithms, Swarm intelligence algorithms and Cultural and Social Evolution algorithms, Evolutionary algorithms (EAs) can be termed as search based stochastic optimization algorithms inspired by Darwinian Theory of evolution. The main stream of algorithms developed

under the umbrella of evolutionary algorithms include, Genetic Algorithms[78], Evolutionary Strategies[79], Genetic Programming[80,81] and Evolutionary Programming[82].

Swarm intelligence can be defined as[83] "a property of a system of unintelligent agents of limited individual capabilities exhibiting collective intelligent behaviour". A swarm can be considered to be a loosely structured collection of interacting agents[83]. Swarm Intelligence algorithms can also be integrated into the stream of evolutionary algorithms, as these algorithms also embody emergence and self-organization behaviour[84]. Some of the most popular swarm intelligence based algorithms are Artificial Bee Colony Optimization[85], Particle Swarm Optimization[84], Ant Colony Optimization[86,87], Quantum Inspired Evolutionary Algorithms[88] and Artificial Immune System[89], Whale Optimization Algorithm (WOA)[73], Biogeography Based Optimization[72]. Based on the swarm behaviour, various algorithms have been developed to solve complex real world problems.

The Cultural Algorithm[90,91], Society and Civilization Algorithm[92] and Social Evolution[93] algorithms are another set of swarm based algorithms which are inspired by the culture, human interactions, biases and human behaviours of the people in a society.

Although, a good number of nature inspired evolutionary algorithms exist, no one algorithm is better than the others when compared across all optimization problems. According to No Free Lunch Theorem, for any algorithm, any elevated performance over one class of problems is exactly paid for in performance over another class. Because of the limitation of individual nature inspired algorithms, researchers have developed hybrid algorithmic solutions by combining the features of two or more algorithms to solve complex real world problems. Examples of such hybridized algorithms include Genetic Simulated Annealing Algorithm (GASAA)[94], Hybrid Immune Algorithm that combines the benefit of Artificial Immune Algorithm and Hill Climbing local search algorithm[95] etc.

The Nature Inspired Algorithms have been applied to various applications such as numerical optimization, constraint optimization, engineering optimization, image processing, bioinformatics, software engineering, numerical optimization, economics, and power distribution applications. Recently, researchers have also started exploring to apply Nature Inspired computing algorithms to

address dynamic and real time complex problems in the areas of Cloud Computing and Internet of Things.

All the proposed optimization problems are NP-hard where optimal solution cannot be achieved in polynomial time using traditional method. Because of this compelling reason researchers have attempted to solve these problems using some of the NIC techniques as these techniques can find optimal or near optimal solutions in reasonable time.

5.2 Datasets

1.Optimization of Energy Consumption In Mobile Devices By Efficient Computational Offloading and Optimal Resource Allocation in Multi-Tier Multi-Access Edge Computing Systems in 5G Heterogeneous Networks using recent Nature Inspired Computing Techniques.

For this research objective, the datasets given in Huynh,Luan NT,etal.[**29**] will be used so as to facilitate comparison of our implemented NIC techniques.

2. **Optimization of Resource Allocation Scheme for 5G Cloud Radio Access Network (5G-CRAN) using recent Nature Inspired Computing Techniques.**

For this research objective, the datasets are taken from Ado Adamou Abba Aria et.al. [**42**] will be used so as to facilitate comparison of our implemented NIC techniques.

3.Optimization of Network Slice Resource Management problem in heterogeneous environment in 5G Networks using recent Nature Inspired Computing Techniques.

For this research objective, data sets are taken from Bin Han et.al[**50**] will be used so as to facilitate comparison of our implemented NIC techniques.

Where ever required we will also synthesize additional datasets with different complexities for further analysis.

6. References

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